Lifting the lid on Land Cover/ Use change and its effects on local ecosystems in the Bamenda highlands of Cameroon

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***Abstract*. The goals of this study were to use remote sensing and a Geographic Information System to track land use and cover change in Cameroon's Bamenda highlands and to assess the effects of these changes on the local ecosystem. Supervised classification using the maximum likelihood classification algorithm was used to extract information from Landsat time series images from 2000 to 2018. The classification was relatively acceptable and effective in detecting land-use changes in the area. Between 2000 and 2010, farmland increased by 10.29%, and by 2018, it had increased by 14.39%. Similarly, plantations expanded by 15.07 km^2 (4.1%) between 2000 and 2010, reaching 20.51 km^2 (5.58%) by 2018, while built-up areas increased by 0.51% between 2000 and 2010, reaching 1.43% by 2018. These increases came at the expense of forest, savannah, and waterbodies, which were reduced by 3.93%, 10.33%, and 17.17%, respectively. Savannah had a strong negative correlation with a built-up area (R^2 = 1), and plantation area (R^2 = .98). As a consequence, the increase of built-up areas and plantation farms could be at the cost of the reduction in savannah and forestlands. On the whole, increased deforestation, growth in plantations, built-ups, and farmlands, have had an impact on the area's ecosystem structure and functions. The findings are critical for developing environmental management policies and ecological integrity of the area. Water, energy, food security, climate mitigation, and agroecological sustainability policies, as well as their synergies and tradeoffs in the context of sustainable development goals, are important research areas.**

***Keywords*: Bamenda highlands; land use/cover change; remote sensing; maximum likelihood classification; Landsat time-series imageries; Geographic Information System**

I. INTRODUCTION

Humanity is at a crossroads. It has entered a new geological epoch, the Anthropocene, where man constitutes the largest driver of environmental change on Earth. Man has crossed several planetary earth boundaries that govern the system's stability [1], and thus its ability to provide essential support functions, fundamental conditions for good and healthy lives, and, ultimately, a stable state of the planet. The negative consequences of changing land use and land cover are enormous, including climate change [2, 3], changes in the hydrological cycle, and global environmental degradation risks [4]. The livelihoods of rural people are inextricably linked to the landscapes in which they live, and they are especially vulnerable to changes in these landscapes [5]. Land cover change refers to a change in certain continuous characteristics of the land, such as vegetation type, soil properties, and so on, whereas land-use change refers to a change in how humans use or manage a specific area of land [6].

In much of Africa, landscapes are subject to increasing pressures from anthropogenic and natural processes. Ongoing and accelerated change in land use and national and local economies often translates to increased vulnerability for both local natural resource-dependent communities and the biodiversity and ecosystem services they depend on [7]. Belo Sub Division (BSD) is part of the Bamenda Highlands and is known for its agriculture, beautiful rolling mountains and hills, and diverse natural ecosystems. It is the administrative sub-division with the highest population density in the Boyo Division, with over 88,664 people living in both the hills and valleys [8]. The region is facing a number of environmental threats to its way of life, including changes in land use and land cover (e.g., agricultural expansion and deforestation) and frequent natural disasters (e.g., landslides, severe storms, and drought). Remotely sensed data from space may be especially useful in areas where recent and reliable spatial information on LULC change is lacking. More actions are required to overcome the current challenges.

Data from earth-sensing satellites have become increasingly important in mapping the Earth's features and providing objective information about LULC features in recent years. As a result, accurate information on LULC and their changes is critical for decision-makers and scientists in sustainable development, natural resources, global change research [9], and sustainable livelihoods. This data is regarded as a critical input for a variety of applications, including water resource management [10], natural hazards analysis [11], land change assessment [12], and CO2 emission studies [2], which constitute some of the essential variables of livelihood change.

Researchers have long used remote sensing technology to extract current and previous land use and land cover (LULC) information and to provide a robust inventory of LULC changes [13]. Recent advancements in remote sensing tools, as well as their integration with Geographic Information Systems, contribute to the success of the technique and introduce a broader scope of research, including LULC change detection, modeling, and prediction [14]. Every change in land cover is reflected in the radiance value captured by a remote sensor, such as a satellite image sensor [15].

Later, radiance value variation is measured by comparing multi-temporal satellite images or aerial photographs [16], and LULC maps are created to detect changes. Many LUCC studies have been carried out successfully using remotely sensed data [17]. Calderón-Loor et al. [18] assessed LUCC in Australia using Landsat images from 1985 to 2015, and the results demonstrated that the authors' method is feasible for monitoring LUCC over large areas. From 1976 to 2003, Mallupattu and Reddy [19] studied LUCC in urban areas using remotely sensed data and discovered that it was significant. Due to the scarcity of historical ground-truth data and the high computational costs associated with producing it, the production of consistent, high-resolution land-cover maps over large areas has been hamperedLand use models generated by RS analyses can investigate the transition potentials of various LULC types for a given set of driver variables [20]. This data can then be used to forecast future LULC data for a study area.

Unfortunately, comparing the results of such change maps is difficult because they differ in terms of the type of satellite data used, the observed period, the methods for generating and validating such products, the LULC change classification scheme used, the spatial resolution of the map, the geographic domain covered by the map, the mapping project's objectives, and the organizations responsible for creating LULC maps. Furthermore, most research on LULC and its effects on local ecosystems in Sub-Saharan Africa has concentrated on

Based on this, we examined LULC dynamics in the BSD from the year 2000 to 2018 and conducted qualitative correlation analyses to investigate the relationship between changing LULC and local ecosystems. A better understanding of the complex interactions of these changes over time should aid decision-makers in the formulation of regionally tailored policy interventions that stimulate benefits while mitigating negative consequences by taking into account the trade-offs between economic, environmental, and social objectives in the process of sustainable rural development. The study specifically seeks to answer the following key questions: (1) what are the dynamics of land use/Landover in Belo subdivision of the Bamenda highlands for the past three decades? and (2) what are the consequences/effects of these dynamics on the local ecological system?

The method entails using remote sensing and GIS technologies to process timeline remote sensing data and correlating LULC with changes in livelihood parameters. The information gathered from the above data analyses is expected to inform decision-makers and development practitioners about the magnitude and nature of long-term LULC change in the area, as well as its impacts on livelihood capitals.

II. MATERIALS AND METHODS

2.1. Study Area

Belo Sub Division (~346km2) lies between latitudes $6^{O}\,06'$N and $6^{O}\,20'$N and longitude $10^{O}10'$E and $10^{O}\,32'$ East of the Greenwich Meridian. It is bordered by the Fundong and Njinikom Sub Divisions to the west, Oku and Babessi Sub Divisions to the East, Noni Sub Division to the North, and Tubah and Bafut Sub Divisions to the South (Figure 1). The area was chosen for research because it contains the largest remaining area of Afromontane forest in West Africa. The area is rich in biodiversity, home to the endemic Bannerman's turaco and banded wattle-eye.

The climate is of the warm savannah type, with mean daily temperatures of around 30^{0}C in the dry season, and 20^{0}C in the dry season. The mean annual rainfall ranges from about 200mm to 400mm and is often torrentially accompanied by thunderstorms leading to numerous landslides, especially in August and September [8]. The vegetation is generally made up of montane forests, harboring numerous species of plants and animals. The few streams and rivers in the region take their rise from the Ijim-Kilum Mountain and the headwaters of the Menchum River. A considerable proportion of the Sub Division is covered by savannah grassland used mostly for grazing. The soils are typical of two principal types: modified orthic soils and penevoluted ferrallitic soils, regosolic and lithosolic soils. Farmers usually take advantage of the wet soils for the cultivation of corn, beans, plantains, and huckleberry.

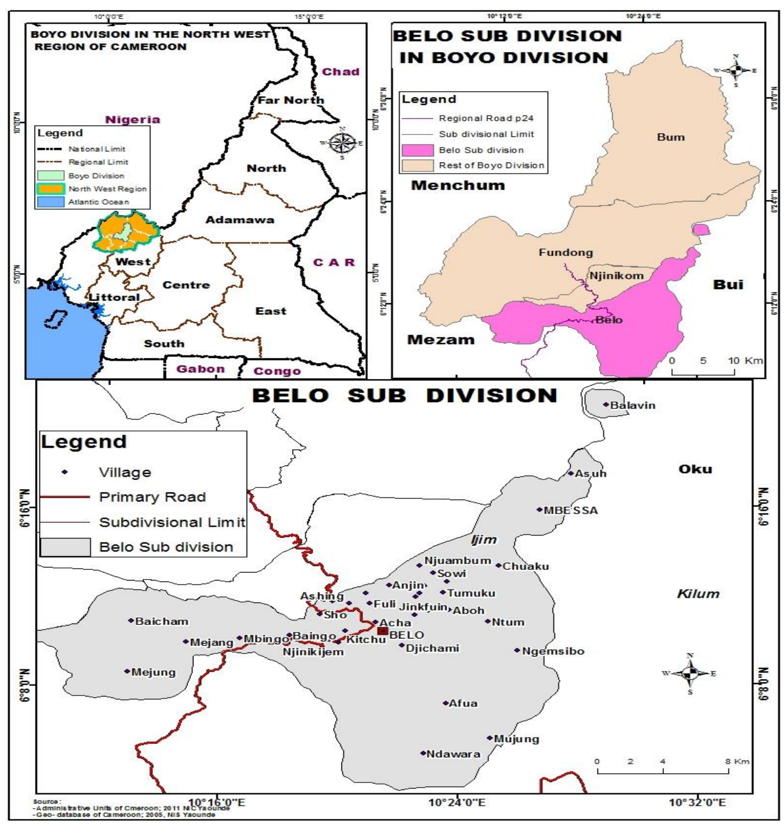


Figure 1: Location of the study area

2.2. Research design and data collection

A cross-sectional research design was used in this study. Data was gathered from both secondary and primary sources.

Because seasonal variability changes the appearance of land use features, which can impact analysis quality, Landsat time series data (2000-2018) were used as secondary data. The images were obtained for free from the United States Geological Survey's (USGS) Earth Resources Observation and Science Center data warehouse (EROS). The selection of Landsat satellite image dates was influenced by the image quality, particularly for those with limited or low cloud cover.

Field observations and ground truthing were collected as primary data using a Geographic Positioning System (GPS) receiver, a Garmin Etrex 10. First, a reconnaissance survey was carried out both in the dry season (November-February) and the rainy season (March-October) between the years 2017 and 2018. This survey provided general information about the study area, helped us understand the significance of land use and land cover change within it, and gathered training profiles for image classification. Discussions with municipal officials and village regents supplemented the information.

2.3. Data Processing and Analysis

The project generated the required LULC change map using pre-existing LULC GIS data layers for the years 2000, 2010, and 2018. All of the bands from the two Landsat scenes were downloaded as separate image files (.tiff) and layer stacked and mosaicked using ENVI 5.1. Following a review of the literature and a lab examination, the 5-4-3 band combination was chosen for the RGB color composite, i.e. band 5 in red, band 4 in green, and band 3 in blue. This combination provided the most information and color contrast, making it easier to distinguish different LULC features [21]. The resulting image was geo-referenced to the WGS 84 datum and the Universal Transverse Mercator Zone 32 North coordinate system using a Polynomial model. Streaming bends and junctions were the most common ground control points. The images were resampled to a pixel size of 30 m 30 m using the Nearest Neighbor method. Radiometric and atmospheric correction [22] were performed to reduce statistical noise and atmospheric extinction affecting image brightness values due to variations in scene illumination, atmospheric conditions, viewing geometry variations, and instrument response characteristics.

2.3.2. Image classification

To generate the required LULC change map, the LULC maps for the years 2000, 2010, and 2018 were recoded into six LULC classes per date (Table 1).

Table 1: Landcover classification scheme

Land use/Cover class	Description
Built-up	Land covered by buildings and other man-made structures. Residential, commercial services, roads, industrial areas, mixed urban or built-up lands
Farmland	Areas that are currently cropped or land that is being prepared for crop production. Physical boundaries are defined broadly to include the main areas of agricultural activity and are not based on exact field boundaries.
Savannah grassland	Non-cultivated areas dominated by herbal vegetation
Mixed forest	Land spanning more than 0.5 hectares with trees higher than 5m and a canopy cover of more than 10%, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agriculture.
Plantations	Mostly tea estates
Water bodies	Lakes, rivers, and streams

The maximum likelihood algorithm provides more accurate results than other classification methods. The maximum likelihood classification algorithm requires a training area to be identified for every class that represents the spectral behavior within every class [23]. Based on the rule, each pixel belongs to a class to which it has the highest probability of being a member [24].

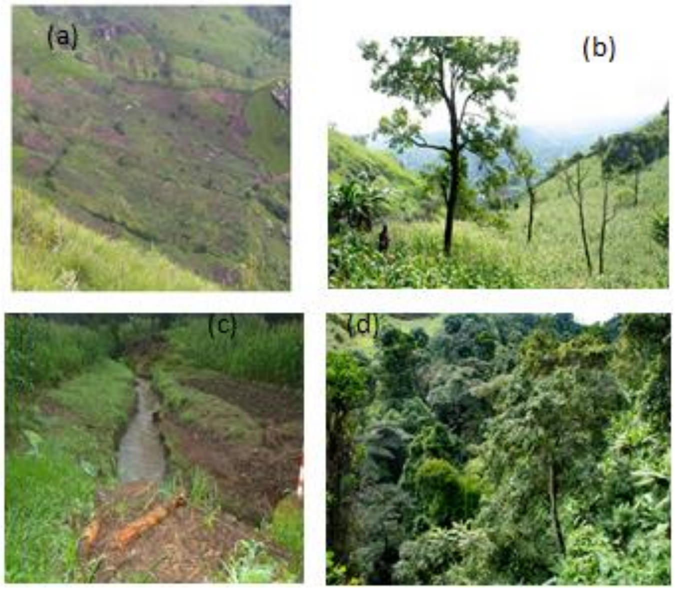
2.3.2. Post-processing

The LULC change map's classification accuracy was then assessed using guidelines from [25, 26]. The goal of map validation was to compare the overall accuracy of the LULC change map to available reference data. Because there was no reference LULC map for the study area between 2000 and 2018, the 2018 classification output was based on ground truth data. Because all three images were classified using the same signature and training information, the 2018 accuracy assessment confidently confirmed the accuracy of the other two, assuming that the land cover remained consistent over time. By constructing a confusion matrix, the final land use classifications of all dates were compared to all available reference data and field information, as well as the author's experience in the study area. A Confusion matrix compares the relationship between known reference data and classification results on a category-by-category basis [27]. Kappa coefficient, user accuracy, producer accuracy, and overall accuracy were all calculated.

III. RESULTS AND DISCUSSION

3.1. Socioeconomic history

Belo sub-division benefited from rapid economic growth during the early years of reunification. Increasing cash crop production, mainly Robusta coffee, and more recently *zea maize* and other subsistence/peasant crops led to the creation of cooperatives to help market agricultural products. Coffee production, for example, exploded in the area making it one of the largest producers of Robusta coffee in the country. However, coffee expansion stagnated since between the late 70s and early 80s as prices plummeted to unbearable levels for a ton of green beans of Robusta coffee. Since then (about half a century), state subsidies and bureaucracy in the area haven't tapped the labor potential of the people. In an attempt to diversify to other sources of livelihood, the population responded with massive extensions in a variety of subsistence crops, dotted all over the study area mostly around settlements, slopes, valleys, and on grazing lands throughout the region (Figure 2)



(a): Farming on the slopes (b): Maize farmlands in the valleys (c): Conversion of riparian vegetation to farmlands (d): Gallery forest

Figure 2: Examples of LULC features in the study area

3.2. Land-cover changes

A consistent time-series land cover classification was performed for the Belo sub-division of the Bamenda highlands from 2000 to 2018. The accuracies of land use classification were assessed (Table 3)

Table 2: Summary of the accuracy assessment report for the 2018 classified image

LULC Type	User's accuracy (%)	Producer's accuracy (%)	Overall accuracy
Built-up	83.3	83.3	0.8837 or 88.37%
Farmland	82.8	96.0	
Forest	100.0	92.3	
Savannah	96.2	96.2	
Water	100.0	100.0	

Variations in classification accuracy may be attributed to temporal or quality differences in remote sensing data. The observed overall agreement for 2000 to 2018 LULC maps to reference data is considered good for general LULC classification schemes and single dates of LULC maps, as it equaled or exceeded 85% [28]. These accuracy assessment results for individual dates of LULC maps are also comparable to what Spruce et al. [29] produced in another multi-date LULC mapping and change detection study. The land use-land cover maps generated by combining remotely sensed image classification and corresponding GIS editing have provided critical LULC information for this study area: Figures 3a&b summarize the results for the analysis of the 2000 imagery

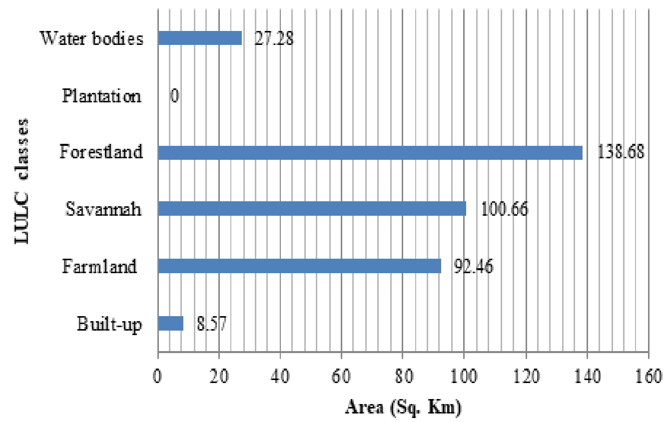


Figure 3a: Area distribution of each LULC type in 2000

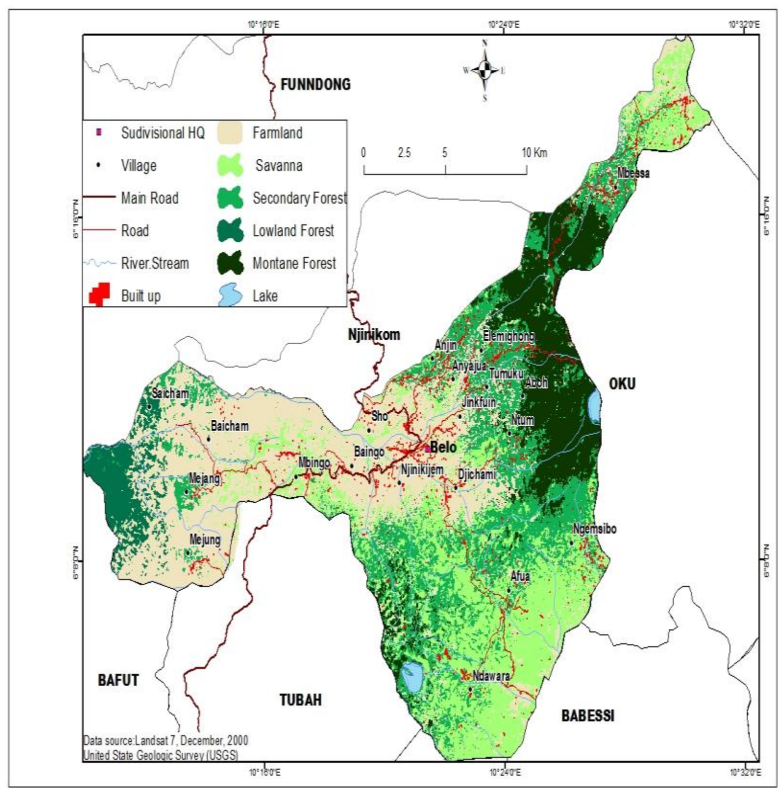


Figure 3b: LULC map following the analysis of the 2000 Landsat imagery.

It is shown that forest covered 37.72% of the land area (lowland forest 4.4%, montane forest 11.57%, and secondary forest 21.75%). Savannah took up a sizable portion of the land (27.38%). Other LULC features included farmlands, water bodies, plantations, and built-up areas, which made up 25.15%, 7.42%, 0.00%, and 2.33% of the area, respectively. Figures 4a and 4b show the results of the Landsat imagery analysis in 2010.

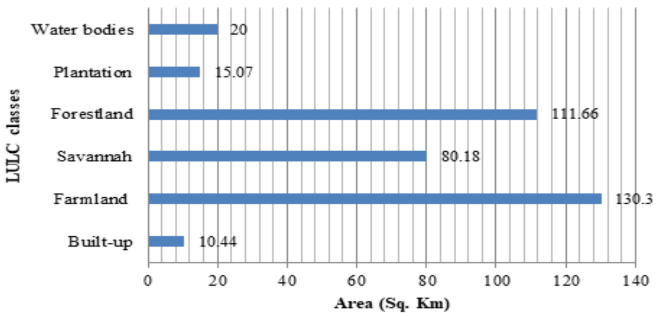


Figure 4a: Area distribution of each LULC type in 2010

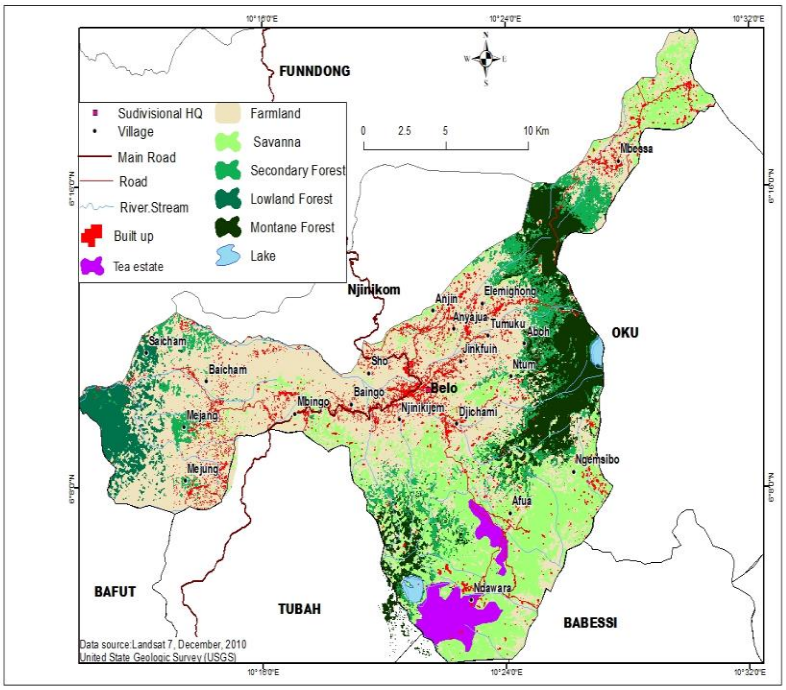


Figure 4b: LULC map following the analysis of the 2010 Landsat imagery

As in the 2000 analysis, forestlands comprised the dominant portion (30.37%) of the land area among which secondary forest covered the maximum of 20.50%, followed by montane (10.16%), and lowland forest (3.71%). Other LULC features namely savannah, farmlands, water bodies, plantations, and built-up areas comprised 21.81%, 35.44%, 5.44%, 4.10%, and 2.84% respectively of the total LULC in the area. Analysis of 2018 Landsat imagery is displayed in Figures 5a&b.

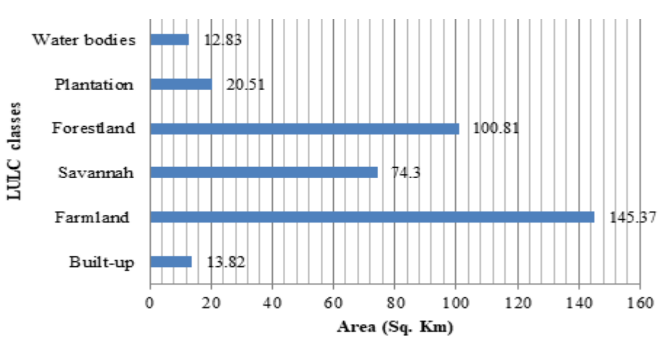


Figure 5a: Area distribution of each LULC type in 2018

The more transitional LULC classes, such as farming (shifting cultivation), built-up areas, and plantations, which can be related to urbanization and swidden cultivation practices, were particularly dynamic, as expected. In contrast, the savannah and forestlands categories, like the savannah, showed a slow decrease in total mapped area, which could be due to abandoned agricultural areas or abandoned agricultural areas reverting to forest.

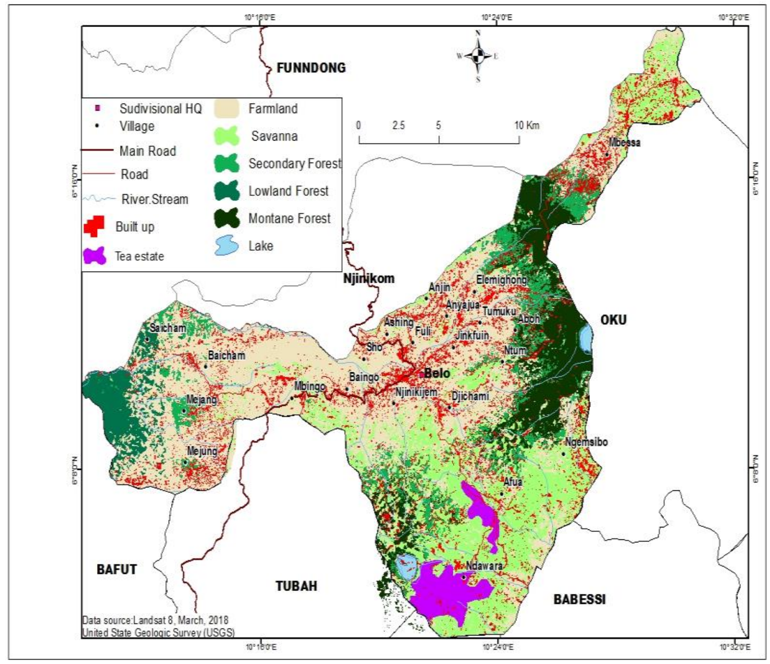


Figure 5b: LULC map following the analysis of the 2018 Landsat imagery

The above figures revealed that plantations, built-up areas, and farmlands increased steadily from 2000 to 2018, while water bodies, savannah, and forestlands declined steadily over the same period. Table 3 is a compilation of the total area and percentage of the area covered by each LULC type.

Table 3: LULC statistics between 2000 and 2018

LULC Classes	2000		2010		2018	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Built-up	8.57	2.33	10.44	2.84	13.82	3.76
Farmland	92.46	25.1	130.30	35.44	145.37	39.5
Savannah	100.66	27.3	80.18	21.81	74.30	20.2
Forestland	138.68	37.7	111.66	30.37	100.81	27.4
Plantation	0.00	0.00	15.07	4.1	20.51	5.58
Waterbodies	27.28	7.42	20.00	5.44	12.83	3.49
Total	**367.65**	**100**	**367.65**	**100**	**367.65**	**100**

Belo's urban land has expanded rapidly as the economy has grown and the city's population has grown. Urbanization will cause significant changes in LUCC, potentially leading to an increase in the destruction of natural habitats. Furthermore, an increasing amount of agricultural land is being converted to urban land use. This could reduce food production and threaten food security in future, everything being equal. Like other sub-divisions in the Bamenda highlands, Belo is an agricultural area and populated. The noticeable change in plantations farmlands and buildups indicate the impacts of anthropogenic activities in the area. Figure 6 shows the change analysis from 2000 to 2018.

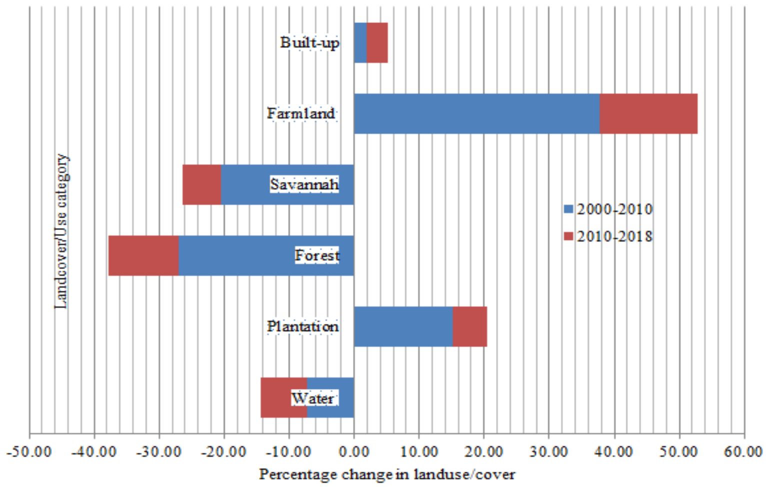


Figure 6: Dynamics in LULC classes: 2000 - 2018

We infer from Fig. 6 that, from 2000 to 2018, a striking negative change was observed for forestlands, savannah, and water bodies, indicating that these LULC types lost more area than they gained. The change was not spatially homogenous. For example, in the Baingo village a total of 62.5% of the individual coffee farms have been converted, at Mbingo, about 41.86% were converted, and at Mbessa village, a huge 74.44% ere converted. The general trend shows a shift in the coffee production sector which was once sporadic and dominated most parts of Belo Sub Division up to the early eighty's. These plantations have been converted to settlements, and other agricultural landuses, especially, subsistence crop production, to meet up with changing times, especially, the challenges of poverty and food insecurity.

On the contrary, there was a sharp positive net change for the farmlands, plantations, and built-up areas. Plantations have increased from 0 Sq. Km in 2000 to about 20.51 Sq. Km in 2018. The Ndawara tea estate has increased to about 20.52km^2. Introduced in 2003, the Ndawara tea estate has completely altered the natural scenery of the Belo subdivision. Many local farming plots, savannah areas, grazing, and part of the local settlements were grabbed and are still being grabbed as the extension of the estate continues. The Ndawara tea estate (~5000ha) is the largest tea plantation in the country, including the factory, vast tea fields, and nursery. Away from the tea estate, in the uplands, plantain farms are gradually emerging in the relatively lower sections of Mbingo II, Mejang, and Mughef villages, spurred by the high demand for plantains in the region and beyond, and the ability of the plantains and bananas to sustained the population during the off farming season in the area.

3.3. Consequences/ Effects of LULC change on the local ecological system

Land-cover change has numerous ecological, physical, and socioeconomic consequences. On the positive side, agricultural expansion may increase food production for a growing population, although it is unsure how productive the last exploited lands will be as they are typically the least favorable. On the negative side is land degradation with its enormous negative consequences.

Belo subdivision has very few wetlands, covering about 0.54% of the area. The most serious threats to wetlands have been their drainage and reclamation for agriculture and the diversion of water supplies for irrigation. Many wetlands have been polluted with domestic sewage, herbicides, pesticides, fertilizers, industrial effluents, and other waste products. Riparian zones have been cleared and farming activities succeeding agricultural practices have led to the siltation of many streams and the disappearance of many.

Riparian zones have been cleared and converted into farmlands (Fig. 7), giving leeway to the siltation of many rivers, reducing them to seasonal streams, and the disappearance of many others.

Figure 7: Farming and Deforestation along the River Meghumi- Njinikijem

Based on recall data from the local population, the above activities and their impacts have contributed to the decline in fishery biodiversity, especially that of the catfish in the area (Fig.8)

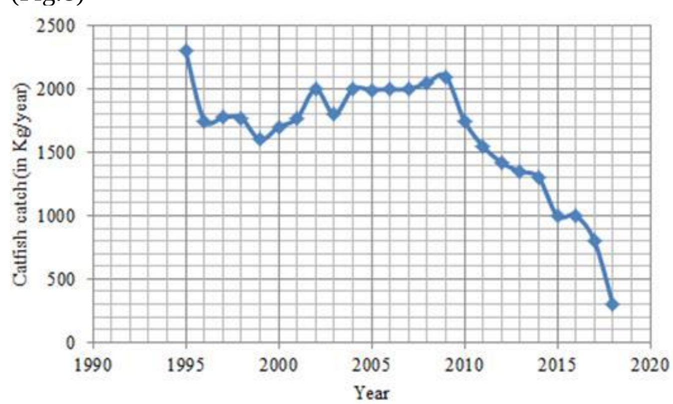


Figure 8: Catfish catch in Belo subdivision (2000-2018)

Floods & Soil Erosion: The number of floods recorded in the 1980s and 1990s, according to recall data from the area is on average, five times less than the number recorded in the 2000s and 2018s. Forest clearing for agriculture, firewood and charcoal production reduced forest area significantly over the last 18 years. Farmland activities are the first known forest degradation drivers even though deforestation deriving from farmland and other LULC types is a complex problem [30] in tropical Africa. In Cameroon, from 0.01% between 1990 and 2000, the forest degradation rate multiplied by between 2000 and 2005 [31]. Within the last three decades, it has been aggravated by extractive activities and urbanization. Fieldwork showed that 31% of soil degradation in most upland areas of the Belo sub-Division was caused primarily by farming activities.

However, uncontrolled grazing is fast depleting the riparian vegetation/ecosystems. Our field investigations revealed that 44% of soil degradation in most upland areas of the Belo sub-Division was caused primarily by overgrazing. Cattle rearing was a live long activity of the Mbororo communities in the Belo subdivision. Today, it has expanded to include a wide portion of the local population as they diversify to alternative forms of livelihood following recent global changes. Animal units in excess on rangelands, together with padlocking and transhumance practices over time have led to the destruction/degradation of marshy vegetation and grasslands. In the uplands areas, cattle tract topography is formed which in the long run, as a result of continuous runoff has led to gully topography. Generally, the net present value of the damage cost in 2018 could be estimated to be about US$ 12 million over the past 18-year period. Riparian wetlands are a vital component of an ecosystem. It is worth noting here that wetlands hold between 20 and 30% of the estimated global soil carbon (~ 3,900 Pg) [32] despite occupying only 5–8% of land surface [33]. The anaerobic conditions, characteristic of wetland soils, slow the decomposition of organic matter and lead to its long-term accumulation as high amounts of carbon stock.

Bush fires have long been identified as the quickest form of forest clearing. It is a common practice in the area that beginning dry season, forests and grasslands are burnt to provide better feed for the increasing population of cattle. Such practices rightly play a key role in shaping ecosystems by serving as an agent of renewal and change. However, fire can be deadly, destroying homes, wildlife habitats, and timber, and polluting the air with emissions harmful to human health. Fire also releases carbon dioxide, a key greenhouse gas into the atmosphere. In addition, ashes may destroy much of the nutrients and erode the soil, causing flooding and landslides.

Deforestation was also identified to be one of the pillars of LULC changes and degradation in the area. Forest is either felled for crop farming or cattle grazing for fuelwood production. Our field investigations revealed that about 25% of soil degradation in most upland areas of the Belo sub-Division was caused primarily by deforestation for fuel wood and plank. The loss of the montane forests as such is important not only because of the potential extinction of species but because of the impact on the people of the area. For the people of the area, the forest is a source of water, firewood, timber, fibers, and medicinal plants, food (honey, mushrooms, fruit, and animals). It also plays an important role in local tradition and culture. However, montane forests have maintained a relative balance due to the increase in the number of protected areas. Another reason for the relative stability of montane forests in the area is the indigenous belief wherein some parts of the forest are considered sacred forests for rituals.

Land use and land cover activities have slowed as a result of the ongoing Anglophone crises. Turf grasses and forests around the roadsides have been cleared or burned by the military forces for safety, as they believe that these turfs serve as zones of ambush for their opponents. On the other hand, human-introduced forests such as the eucalyptus trees, cypress trees, and other related trees found on roadsides before the crisis have been felled down and used as road barricades by the militias. The loss of trees and other vegetation as such can cause climate change, desertification, soil erosion, a decline in crop production, flooding, increased greenhouse gas emissions, and a host of other environmental and social problems for already suffering indigenous people. The harmful effects of ecosystem service degradation are borne disproportionately by the poor, contribute to growing inequities and disparities across groups of people, and are sometimes the primary cause of poverty and social conflict. This suggests that ecosystem changes, such as increased food production, haven't helped many people get out of poverty or hunger, but these changes have harmed other people and communities, and their plight has largely gone unnoticed.

IV. CONCLUSION

Using remote sensing and GIS techniques, a LULC change mapping study for the Belo subdivision of the Bamenda Highlands was carried out. Landsat imagery (from 2000, 2010, and 2018) was triangulated with ground truth data to create the dataset. The analysis of the resulting LULC maps revealed that, while some LULC classes (e.g., forest cover, waterbodies, and savannah grassland) experienced continuous decline over time, others (e.g., farmlands, plantations, and built-up areas) experienced continuous increase. However, between 2010 and 2018, the rate of land cover conversion slowed, owing to the enormous efforts of both local and international non-governmental organizations. Not all of the observed changes appeared to be of a permanent nature, but instead some form of ephemeral or transitional change associated with agricultural and/or forestry practices. Collectively, these changes have led to land degradation and extreme weather events such as droughts and siltation surges, and salinization, which may in turn, add to other negative social impacts such a malnutrition, cholera/dysentery, and respiratory diseases caused by atmospheric dust from wind erosion and other air pollutants.

The findings serve as a baseline for future water, disaster (landslide), forest, and agricultural management efforts in the area. The project's 2000-2018 LULC change maps, on the other hand, could be refined with higher resolution imagery and advanced modeling approaches like artificial intelligence and spatial statistical models. Important research areas also include the political economy of designing and implementing water, land use, energy, food security, climate mitigation, and agro-ecological sustainability policies, as well as their synergies and tradeoffs in the context of the Sustainable Development Goals. The state and management of ecosystem services are also major factors influencing prospects for poverty reduction in the area.

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